SocialTrust: Adaptive Trust Oriented Incentive Mechanism for Social Commerce

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***Abstract*—In the absence of legal authorities and enforcement mechanisms in open e-marketplaces, it is extremely challenging for a user to validate the quality of opinions (i.e. ratings and reviews) of products or services provided by other users (referred as advisers). Rationally, advisers tend to be reluctant to share their truthful experience with others. In this paper, we propose an adaptive incentive mechanism, where advisers are motivated to share their actual experiences with their trustworthy peers (friends/neighbors in the social network) in e-marketplaces (social commerce context), and malicious users will be eventually evacuated from the systems. Experimental results demonstrate the effectiveness of our mechanism in promoting the honesty of users in sharing their past experiences.**

***Keywords*-Trust; reputation systems; electronic commerce; incentive mechanism;**

I. Introduction

In e-marketplaces, buyers and sellers conduct transactions through the electronic media, such as the Internet. Despite the convenience e-marketplaces bring, the uncertainty inherent in open markets along with the participation of self-interested agents (e.g. buyers and sellers) reduce buyers' confidence in conducting transactions with unknown sellers, thus discouraging them from actively participating in e-marketplaces. Reputation systems [16], where buyers publicly share their past experiences with sellers in the form of opinions (e.g. ratings and reviews), is an effective way to justify and predict the behavior of sellers in e-marketplaces. However, as some buyers may provide untruthful ratings to promote some sellers or demote high quality sellers, the effectiveness of reputation systems can be jeopardized. To address this problem, incentive mechanisms, e.g. [7], [23], have been designed to supplement reputation systems, by motivating buyers to provide truthful ratings.

On the other hand, recently, it has become increasingly popular for users to gather information from their personal social networks, and use this information to make purchase decisions in e-marketplaces. Driven by behavioral psychology, buyers tend to value and trust their friends' or acquaintances' opinions about products or services [5]. This phenomenon is more significant in e-marketplaces due to reputation lag [9] as buyers cannot physically touch and evaluate the products before payments and delivery. Consequently, *social commerce* emerges in e-marketplaces [21], where buyers are more likely seek opinions about products or sellers from their social communities [11]. As shown in the literature [10], social commerce can increase both the buyers' purchase satisfaction, and the sellers' revenue. However, the quality of opinions from the users' social network might vary because of two reasons: 1) advisers in the social network might not necessarily provide opinions of high quality; 2) in a same user's social network, different advisers have different degrees of trustworthiness [11].

We address the problem of untruthful opinions in the context of social commerce by designing an incentive mechanism, called *SocialTrust*, by taking advantage of the agents' social network in an e-marketplace. SocialTrust aims to reward honest behaviors while punishing malicious agents. Our key intuition is that an e-marketplace cannot achieve its potential unless its members collaborate by providing truthful information and assisting each other in ridding the community of the deceitful agents. Given the collaborative behavior of buyers, SocialTrust mainly consists of two components. One is, an *adaptive credibility threshold adjustment*, which depends on the central server to monitor the market performance, and adaptively adjust the honesty threshold for buyers in the system. Defining the threshold for acceptable level of honesty of advisers is challenging, since inappropriately setting thresholds would filter away possibly good advice, or the opposite - allow malicious buyers to badmouth good services. The second component is a *voting mechanism*, where the central server promotes the most credible advisers to the role of brokers, and punishes the least credible advisers.

Experiments with a simulated e-marketplace validate the effectiveness of the proposed SocialTrust in eliciting honest behaviors of advisers in providing opinions. They further show the efficacy of our mechanism in the bootstrapping phase, where new buyers join the e-marketplaces and lack personal social networks as well as past experiences with sellers.

II. Overview of the SocialTrust Mechanism

In the proposed SocialTrust mechanism deployed in the e-marketplace, we can assume that each buyer (equipped with an agent) has a set of other buyers (called advisers) in her social network. For example, the buyer may choose advisers from her social network (e.g. Facebook). Alternatively (e.g. eBay), the buyer's agent can use the existing so-called "trust metrics" [6], [22] to build and update its social network based on past experiences. In the experiments, to demonstrate the effectiveness of the proposed mechanism, we particularly

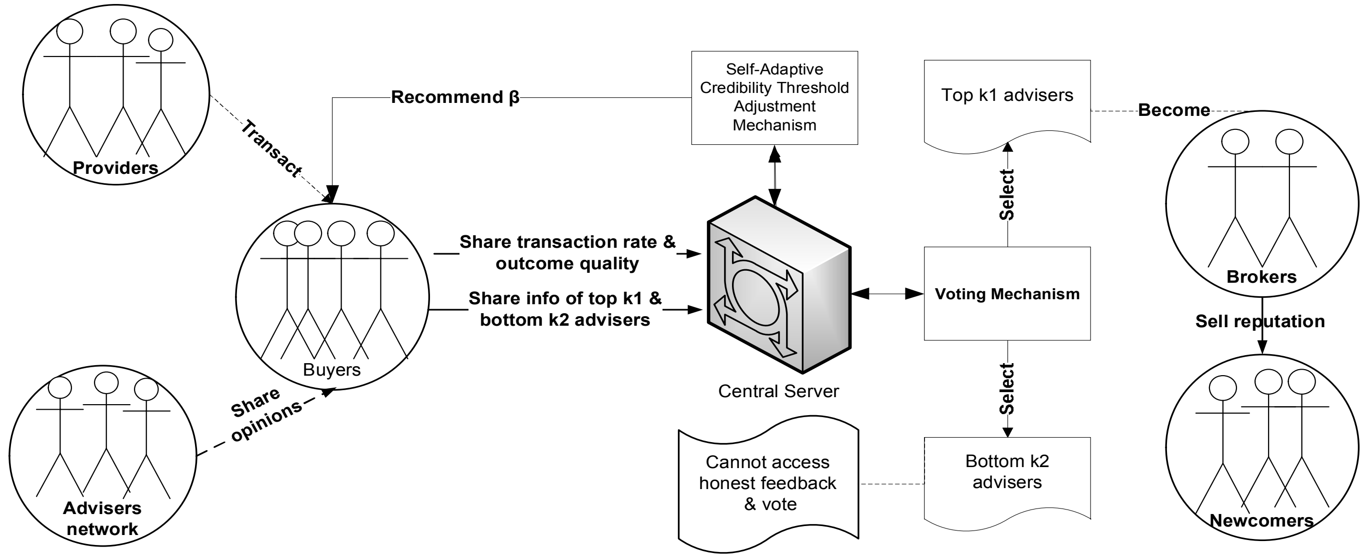

Fig. 1: The overview of the SocialTrust Mechanism

choose to implement the Prob-Cog model [14] for evaluating the credibility of other buyers, and identifying advisers for each buyer. Among all the existing trust metrics, we believe that Prob-Cog is more suitable for our social commerce context since each agent evaluates other buyers' credibility on reporting their experience according to the buyer's behavioral characteristics and preference, which mimics the process of making friends in humans.

Given the buyers' social network and the corresponding credibility values of advisers in the network, SocialTrust mainly consists of two components: 1) *self-adaptive credibility threshold adjustment mechanism* (called **SACTAM**), which monitors the performance of the e-marketplace, and recommends buyers a credibility threshold according to the market performance. The agent of each buyer then dynamically re-evaluates its social network of advisers according to the new recommended value of the credibility threshold, and 2) *voting mechanism*, which takes two actions: *a)* rewarding the most credible advisers, and *b)* punishing and evacuating malicious advisers. The SocialTrust mechanism is depicted in Figure 1.

To formalize the SocialTrust mechanism, we consider a scenario that in the e-marketplace a buyer c wants to purchase a particular product from a seller P_j. Using the Prob-Cog (or another model), the agent of c, a_c establishes the social network of credible advisers, considering the credibility threshold β adjusted through SACTAM. a_c disseminates a query to the agents of the advisers by inquiring about the overall performance of P_j. The advisers share their previous experiences (i.e. reputation information) about P_j with a_c. After aggregating advisers feedback, a_c decides to conduct business transaction with P_j if it has been predicted trustworthy.

In SocialTrust, the agent of each buyer periodically submits two lists of advisers to the *central server*, including the list of the k_1 most credible advisers, and the list of the k_2 least credible advisers. The central server exploits the *voting mechanism* to generate a complete credible ordering over all the advisers submitted by buyers. It then rewards the k_1 most credible advisers, and punishes the k_2 least credible advisers (considered as malicious advisers). Specifically, the most credible advisers are promoted to the role of *broker* in the system. In this case, aside from the social welfare (i.e. fame and status), brokers can earn economic profits by selling reputation information to other buyers in need, such as the newcomers who newly join the e-marketplace, and have few advisers. For the least credible advisers, the central server deprives them from participating in the voting mechanism, and reveals their identity to other buyers in the e-marketplace. Consequently, it would be difficult for them to collect reputation information from others. This is mainly because sharing truthful information is costly, and buyers are reluctant to share information to malicious advisers as their activities would not benefit the system.

In addition, the agent of each buyer submits the number of conducted transactions and the overall satisfaction degree on transaction outcomes to the central server, which compiles this data, calculates a new optimal for the e-marketplace credibility threshold β, and communicates it back to the agents. a_c then re-visits the social network of c, and filters away advisers with a credibility degree below a new recommended threshold value.

III. SACTAM: Self-adaptive Credibility Threshold Adjustment Mechanism

Inspired by the existing electronic commerce quality models[1] [1], [3], [19], we consider three factors that contribute to performance of e-marketplaces, including, 1) market liquidity

[1]Different from other approaches, we ascribe the performance of the e-commerce system only to the quality of its participants (buyers and sellers) in conducting transaction.

(denoted by $Mliq$), 2) information asymmetry, and 3) buyers satisfaction.

Market liquidity describes a marketplace's ability to facilitate trading of the products promptly without transaction cost [4]. It also denotes the ability of buyers to find products with desirable features, when needed. However, the open nature of e-commerce, the existence of variety of products with competing features, and the lack of the honesty enforcement mechanism make buyers uncertain in discovering the best-suited transaction partners (i.e., trust-wise and profit-wise), thus affecting the liquidity of the market.

Information asymmetry measures whether a buyer has sufficient information to make rational purchase decision in the e-marketplace. Higher information asymmetry is particularly salient in online environments. The buyers suffer from the risk of purchasing low quality products, which differ from the descriptions claimed by sellers. The availability of credible advisers can effectively reduce the information asymmetry [20].

buyer satisfaction can be measured using the ratio of transactions with successful outcome to all the transactions conducted by buyers.

In SocialTrust, through the SACTAM mechanism, each buyer can further justify her social network of credible advisers by considering the overall performance of the e-marketplace. For example, a marketplace with poor performance might imply that a considerable amount of advisers and sellers might be malicious. In this case, each buyer might want to carefully check other buyers' qualification as her advisers by increasing the credibility threshold β.

We denote $\text{SuccessNum}_{(c)}$ as the number of satisfactory transactions conducted by a buyer c within a time period between $t - \Delta t$ and t, $\text{transactionNum}_{(c)}$ as the number of all the transactions conducted within the same period, and $\text{purchaseNum}_{(c)}$ as the number of transactions that c initially intended to perform within Δt.[2] Thus, we can formulate the *transaction success rate* and the *transaction rate* of the buyer c denoted by $tsr(c,t)$ and $tr(c,t)$ for the time period Δt as follows:

$$tsr(c,t) = \frac{\text{SuccessNum}_c}{\text{transactionNum}_c} \tag{1}$$

$$tr(c,t) = \frac{\text{transactionNum}_c}{\text{purchaseNum}_c} \tag{2}$$

To accurately adjust β, the central server should have a global observation of the system performance. So, each buyer c is asked to periodically share their $tsr(c,t)$ and $tr(c,t)$ with the central server. The values of $tsr(c,t)$ and $tr(c,t)$ reflect the behavior of participants in the e-marketplace. For example, having a high transaction rate $tr(c,t)$ but a low transaction success rate $tsr(c,t)$ signifies the situation in which buyer c is misled by dishonest advisers in her network; therefore, it could not find high quality sellers. Given these quality metrics, we propose the performance measure for e-commerce systems as:

$$Q(t) = \frac{2 * tsr(t) * Mliq(t)}{tsr(t) + Mliq(t)} \tag{3}$$

where $tsr(t) = \frac{\sum_{c=1}^{n} tsr(c,t)}{n}$ and $Mliq(t) = \frac{\sum_{c=1}^{n} tr(c,t)}{n}$ are the average of all $tsr(c,t)$ and $tr(c,t)$ shared by buyers at time stamp t, and $Q(t)$ is the *harmonic mean* of the e-commerce quality metrics described above. Since the performance of the marketplace is a function of these quality metrics, we use a harmonic mean to balance them by mitigating the impact of the one with a larger value and aggravating the impact of the other with a lower value.

We denote $op(t) \in \{\beta = \beta - \beta_0$ as, op_1, $\beta = \beta + \beta_0$ as, op_2, $\beta = \beta$ as, $op_3\}$- the recommended operations on β for a time stamp t for all buyers. Noted that β_0, resides within $[0,1]$, is a constant, and is used to adjust β in each operation.

At the end of each time stamp t, the central server examines the changes of $Q(t)$ in the last time period $[t - \Delta t, t]$, and manipulates β to improve the $tr(c)$ and $tsr(c)$ of buyers in their future purchases. That is, if $|Q(t) - Q(t-1)| > \delta$ (δ is a small value serving as the trigger threshold), the central server will start the adjustment by strategically choosing one of the two operations, op_1 and op_2. On the contrary, at time t if the $|Q(t) - Q(t-1)| \leq \delta$, the central server will not adjust β by recommending op_3.

The new value of β recommended to the buyers for the next time period $t + \Delta t$ is formulated as follows:

$$\begin{array}{ll} \text{if} & Q(t) - Q(t-\Delta t) > \delta \\ \text{then} & op(t+\Delta t) = op(t) \\ \text{if} & Q(t) - Q(t-\Delta t) < -\delta \\ \text{then} & op(t+\Delta t) = -op(t) \\ \text{if} & |Q(t) - Q(t-\Delta t)| \leq \delta \\ \text{then} & op(t+\Delta t) = op_3 \end{array} \tag{4}$$

Note that, the central server records the performance measure $Q(t)$ at each time stamp t. In each following time period, the central server will check which operation should be recommended again, by comparing the recorded value with that of the current time period.

IV. Voting Mechanism

To discourage advisers from providing malicious opinions (i.e. reputation information), we propose a voting mechanism. In the voting mechanism, the agent of each buyer estimates the credibility of her neighboring advisers in her social network based on the Prob-Cog model and the SACTAM mechanism. Then each agent submits two lists of advisers, including the k_1 most-credible and k_2 least-credible advisers to the central server. These lists are considered as votes provided by each buyer. Finally, the central server aggregates the votes from all the buyers according to the *Borda count voting* procedure presented in this section.

A. Voting Process

Given a set of advisers A, each buyer c submits a list of the k_1 most credible advisers L^C_{high} and a list of the k_2 least credible advisers L^c_{low} in a decreasing order of credibility.

[2] We assume that each buyer has a set of pre-defined purchase missions such that each buyer enters the market to buy certain products.

Motivated by the definition (8.1) in [13], we define the Borda count voting mechanism to aggregate multiple disparate opinions as follows:

Borda Count Voting Mechanism: The central server is given a set of buyers $Par = \{c_1, c_2, \cdots\}$. The vote of each c_i consists of two lists: $L^{c_i}_{high}$ contains k_1 advisers with the highest credibility, and $L^{c_i}_{low}$ indicates a set of k_2 advisers with the lowest credibility. Considering all buyers' votes equally, for each $L^{c_i}_{high}$, the central server awards k_1 positive points to the most credible adviser, $k_1 - 1$ positive points to the second most credible one, and so on. Similarly, for $L^{c_i}_{low}$, the central server assigns k_2 negative points to the least credible adviser, $k_2 - 1$ negative points to the second least credible one, and so on. The winning set, L^{Par}_{high}, represents the social preferences (i.e. the favor of the majority), and advisers with the largest positive points in L^{Par}_{high} are recognized as the most credible advisers in the system. Accordingly, the advisers with the largest negative points in the set, L^{Par}_{low}, are chosen as the least credible advisers in the system.

The total positive points and negative points that a voted adviser a_j gains are denoted by $T^{a_j}_p$ and $T^{a_j}_n$ as follows:

$$T^{a_j}_p = \begin{cases} \sum_{i=1}^{|Par|} \mu_{(a_j \in L^{c_i}_{high})}, & \text{if } a_j \in L^{Par}_{high} \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

$$T^{a_j}_n = \begin{cases} \sum_{i=1}^{|Par|} \mu_{(a_j \in L^{c_i}_{low})}, & \text{if } a_j \in L^{Par}_{low} \\ 0, & \text{otherwise.} \end{cases} \quad (6)$$

where $\mu_{(a_j \in L^{c_i}_{high})}$ and $\mu_{(a_j \in L^{c_i}_{low})}$ refer to the number of positive and negative points to adviser a_j according to c_i's two lists, respectively. L^{Par}_{high} and L^{Par}_{low} denote the sets of advisers that have ever been voted by buyers in Par in the k_1 and k_2 respectively. Given the positive points and negative points of advisers calculated from Equations 5 and 6, an adviser $a_j \in L^{Par}_{high}$ (i.e. candidate of brokers) would be selected by the central server as a broker if she is in the highest k_1 of $T^{a_j}_p$ value. Similarly, an adviser $a_j \in L^{Par}_{low}$ (i.e. candidate of malicious advisers) is chosen as a bottom adviser (i.e. malicious advisers) if she is one of the highest k_2 of $T^{a_j}_n$ value. Thereafter, an adviser could be in the status of: 1) a broker, 2) a malicious adviser, 3) a candidate of brokers or malicious advisers, or 4) has never been voted by a buyer in Par in either k_1 or k_2 list.

B. Initialization of k_1 and k_2

Setting proper k_1 and k_2 is important. While a large value for k_1 or k_2 resides more advisers in the third status, a small value for k_1 or k_2 may hinder advisers' incentives to behave honestly. In order to adjust the value of k_1 and k_2 properly, $k_1 + k_2$ should be no more than the expected number of advisers of each buyer. First of all, let us estimate the expected number of advisers for each buyer. Suppose there are M sellers and N buyers in the system, and each seller P_j has conducted transactions with N_j buyers. Then the expected number of advisers for a buyer, $\overline{N}_a$, can be calculated as:

$$\overline{N}_a = [1 - \prod_{j=1}^{M}(1 - \frac{N_j}{N})] \times N \quad (7)$$

where $1 - \prod_{j=1}^{M}(1 - \frac{N_j}{N})$ is the probability that two buyers have at least one common seller with whom both of them have conducted transactions. Therefore, the first constraint in setting the two parameters is: $k_1 + k_2 \leq \overline{N}_a$.

Initially, we set $k_1 = k_2 = \overline{N}_a/2$, and then the two values will be updated according to the *Pareto principle* (also known as the $80/20$ $rule$) [2]. It states that roughly 80% of the effects come from 20% of the causes. Therefore, in our case, we tune $k_1 \approx 0.2 \times |L^{Par}_{high}|$ and $k_2 \approx 0.2 \times |L^{Par}_{low}|$.

C. The Privileges of Credible Advisers

Once advisers have been promoted to the role of *broker*, they bestow with the ability to sell reputation information about sellers to other buyers. When a broker sells information to a buyer not in her social network, the broker can gain some monetary credits, determined by the central server. If the sold information is reported to be untruthful by a buyer, the positive points T_p of the broker will be discounted to a certain extent. If her T_p drops to the half, her role as a broker will be revoked by the central server. The gained credits can be either cashed out or converted to a certain discount in buying products.

D. The Penalty of Malicious Advisers

The identity of the bottom k_2 advisers will be exposed to the members of the e-marketplace, and their votes would not be considered by the central server. Furthermore, buyers would remove them from their social networks.

V. Experimental Evaluations

A. Experimental Settings

The e-marketplace environment used for experiments is populated with self-interested buyers and sellers, and is operated for 22 days. We initialize the e-marketplace with 60 buyers, each of which making maximum 5 requests every day. At the beginning of day 8, new buyers join the marketplace with a probability of 5% and existing buyers will leave the marketplace with a probability of 5%. Buyers (advisers) are divided into two groups: honest buyers (with high credibility), and dishonest buyers (with low credibility). Honest advisers generate ratings that differ *at most* by 0.25 points from their actual ratings. In contrast, dishonest advisers generate ratings that differ *at least* by 0.25 points from the actual experience. For example, if the seller's QoS value was 0.9, then the honest adviser would generate a value between (0.65 and 0.9), and dishonest adviser would generate a value between (0 and 0.64). In this experiment, buyers calculate the credibility degree of advisers and establish their advisers network through the *Prob-Cog* model [14], [15]. Note that other credibility evaluation approaches can be used instead of Prob-Cog.

We assume there exist 100 sellers and 20 product types and every 5 of the sellers supply products with the same features.

Sellers ask the same price for the products. We further assume the utility of each product is a value randomly distributed within [50,70][3]. Half of the sellers, who supply the same kind of product, are high-performance sellers with QoS values in the range (0.7-1.0). On the contrary, low-performance sellers generate QoS value in a range of (0-0.3). For example, if the seller's QoS is 0.3, the utility of its product is 60 and the price is 5, a buyer's *actual profit* of carrying out a transaction with that seller would be $0.3 * 60 - 5 = 12$.

A buyer c selects seller P_j through weighted average of adviser's ratings, $r_{(a_k)}$- which is discounted by a_k's credibility degree CR_{a_k}- and with its own recent experience $r_{(c)}$, as:

$$\tau_{(P_j)} = \omega . r_{(c)} + (1-\omega) \frac{\sum_{k=1}^{n} CR_{a_k} * r_{(a_k)}}{\sum_{k=1}^{n} CR_{a_k}} \tag{8}$$

Buyers subjectively decide to conduct a transaction if $\tau_{(P_j)} > T$ where T indicates the transaction threshold (here, $T = 0.6$). Also, ω is determined based on Equation 18 presented in [17].

A buyer c's *expected profit* of carrying out a transaction with seller P_j can be formalized as follows:

$$Exp_c^{P_j} = \tau_{(P_j)} * V_{P_j} - p_s \tag{9}$$

where V_{P_j} and p_s indicate the utility of the product promised by P_j and the price of the product, respectively. Also, the *loss* of a buyer c in conducting transaction with P_j can be captured as the difference of its expected profit and actual profit $Act_c^{P_j}$, presented as follows:

$$Loss_c^{P_j} = Exp_c^{P_j} - Act_c^{P_j} \tag{10}$$

Note that buyers who are promoted to the role of broker can sell reputation information to other buyers, specifically the newcomers, and charge them 10% of their actual profit.

In this experiment, we assume that buyers actively interact with the central server and voluntarily share their votes, transaction rate and transaction success rate when requested[4].

We conduct comparative experiments in e-marketplace where 50% of buyers are honest and 50% of them are malicious. We evaluate the performance of the e-marketplace in different environmental settings, adopting the fixed $\beta = 0.5$ versus the self-adaptive β calculated through the SACTAM mechanism.

The experiments operate for a period of 22 days and the reported results for each day are the average of 10 runs.

B. Evaluating the SocialTrust Mechanism

We first evaluate the performance of the first component of SocialTrust – the SACTAM adaptive threshold mechanism in improving the quality of the e-marketplace. We measure the *market liquidity* by examining the transaction rate of different groups of buyers. Upon arrival, buyers randomly select sellers based on their promised utility (up to day 2). After acquiring sufficient experiences they establish their social network of trustworthy advisers, adopting different honesty threshold approaches: 1) the fixed β and 2) the self-adaptive β, which is initialized to 0.5. Given the initial setting of β, buyers have a similar transaction rate in the initial days. However we observe that as β increases, the transaction rate of the honest buyers increases while the transaction rate of dishonest advisers decreases, respectively (Figure 2).

From Figure 2 and Figure 3, we notice that in both honesty threshold management approaches, honest buyers have higher transaction rates compared to the dishonest ones. However, comparative results indicate that in a self-adaptive β honest buyers have higher transaction rate than their counterparts in a fixed β approach. Conversely, dishonest buyers have lower transaction rate in the self-adaptive β than their counterparts in the fixed β. The adaptive approach of the central server in adjusting β, based on the quality of marketplaces, results in 1) increase of honest buyers' transaction rate, and 2) detection and isolation of more dishonest advisers.

We further measure the level of *information asymmetry* in the e-marketplace by evaluating the accuracy of buyers in classifying their advisers. As shown in Figure 4, the accuracy of buyers in a self-adaptive β improves consistently and reaches the optimal value as they adaptively re-evaluate their network of advisers based on a new recommended value of β. The performance measures (i.e., precision) reflect the ineffectiveness of the credibility evaluation mechanism with a fixed β in detecting malicious advisers. By comparing the metric of precision for buyers we notice that in the fixed β approach, buyers more significantly rely on dishonest advisers' feedback in their decision making than the buyers in the self-adaptive β approach. Dynamically monitoring and tuning β using the SACTAM mechanism enables buyers to achieve fairly good precision value hence undermining the impact of dishonest advisers. Note that high precision and accuracy values imply that buyers can access honest feedback, which indicates that the e-marketplace has low level of information asymmetry.

In order to measure *buyers satisfaction* rate we compare the transaction success rate, profit and loss gained by different buyers. We notice that honest buyers provided with SACTAM conduct more successful transactions (Figures 6 and 7), and are more satisfied with their transaction outcomes (Figure 5) than other honest buyers in the fixed β approach. Specifically, the profit difference between honest buyers and dishonest buyers with a self-adaptive β is much larger than that of fixed β. The results indicate that in the e-marketplaces in which buyers are equipped with a credibility evaluation mechanism with fixed β dishonest buyers have a good chance of making profit by behaving deceitfully in the environment. This problem is especially important in competitive e-marketplaces where sellers have limited inventories and good sellers are scarce. On the contrary, as many of the dishonest buyers are detected through the SACTAM mechanism, they have a small chance to access genuine feedback and to mislead other buyers with

[3] In this e-marketplace, we consider products as equally important and offer rather similar utility. Dealing with products with different range of utility is remained for future work.

[4] Dealing with different percentages of buyers' participation is left for the future work.

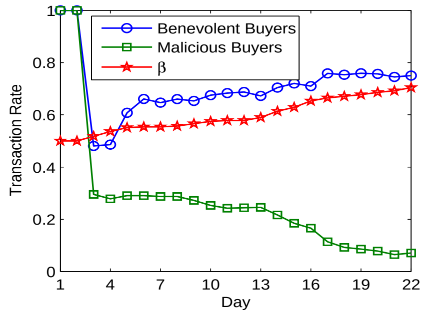

Fig. 2: Transaction Ratios of Buyers with Adaptive β

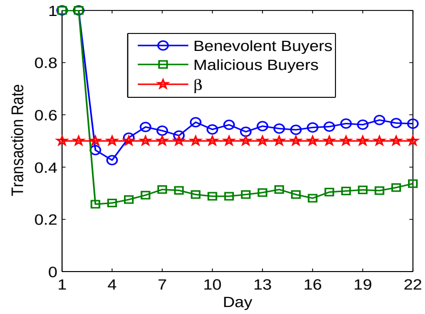

Fig. 3: Transaction Ratios of Buyers with Fixed β

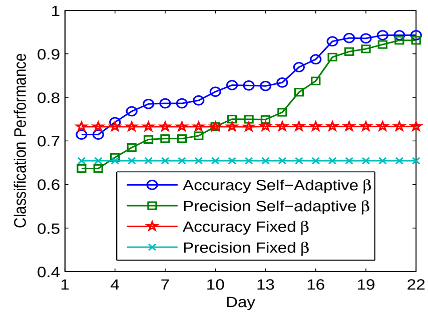

Fig. 4: Accuracy of Buyers in Classifying Advisers

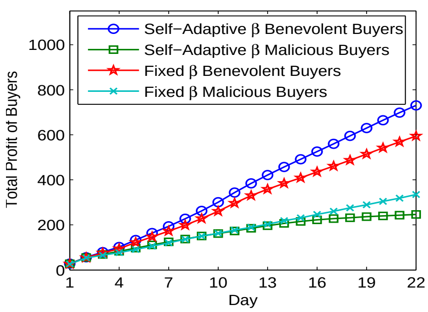

Fig. 5: Profit of Buyers with Adaptive and Fixed β

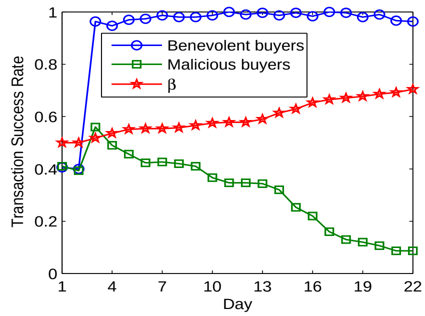

Fig. 6: Transaction Success Rate with Adaptive β

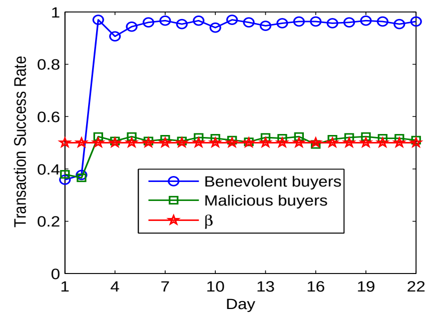

Fig. 7: Transaction Success Rate with fixed β

their corrupted information.

Figure 8 shows that honest buyers in a self-adaptive β approach are able to predict the expected utility of sellers more accurately and gain lower level of loss compared with their counterparts in the fixed β approach.

Next, we evaluate the performance of *voting mechanism* in classifying advisers based on their behavioral disposition. Figure 9 depicts that advisers with the highest level of trustworthiness are selected as brokers; and advisers with a lowest trustworthiness value are listed as malicious advisers. Yet, advisers with an average trust value can perform in this marketplace but they would not have a chance to be promoted to the role of broker.

Figure 10 shows the total profit gained by different groups of advisers. Brokers can gain larger profit than other advisers by selling reputation information to buyers. On the other hand, since the identities of malicious advisers are revealed to the community, they would not be able to access honest feedback, and gain good profit in the e-marketplace. The experimental results indicate that the privileges awarded to brokers and the penalties imposed to malicious advisers promote honesty and discourage dishonesty attitudes in the e-marketplace.

C. Evaluating the Performance of Newcomers Adopting the SocialTrust Mechanism

We evaluate the performance of the new buyers who gradually join the e-marketplace at the beginning of day 8. Newcomers are divided into two groups: those who *purchase* reputation information about sellers from *brokers* up to 4 days before building their advisers network, and the ones who *randomly* select sellers based on their promised utility up to 4 days prior to the establishment of their advisers network[5].

Figure 12 demonstrate that the first group of newcomers (who employs brokers) conduct more satisfactory transactions than the second group of newcomers in the initial days after their arrival (e.g. until round 12). Still, *honest* newcomers of the first group consistently conduct more transaction and have more successful transaction outcomes than *honest* newcomers of the second group (Figures 11 and 12). This is because the brokers recommend high quality sellers to buyers which leads to satisfactory transaction outcomes. Furthermore, as buyers have more experiences with honest sellers than with dishonest ones (Figure 16); therefore, newcomers adopting brokers can more effectively build their own advisers network based on their common experiences with honest sellers in comparison with the newcomers who randomly purchase products and most likely experience some low quality products.
In this experiment, as the behavioral pattern of dishonest newcomers are detected by other buyers (given the self-adaptive β), they are unable to build an effective advisers network and access useful feedback, resulting in a low transaction rate and unsuccessful outcome.

We also measure the satisfaction degree of newcomers by comparing the total profit and loss gained by different sets of newcomers. From Figure 13 we notice that the first group of newcomers who employs brokers obtain larger profits than the other group of newcomers. Also, Figure 14 indicates that newcomers who do not employ brokers consistently lose as

[5]Due to the page limits, we only present the result of self-adaptive β approach.

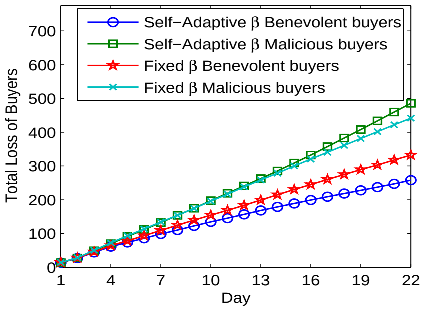

Fig. 8: Loss of Buyers with Adaptive and Fixed β

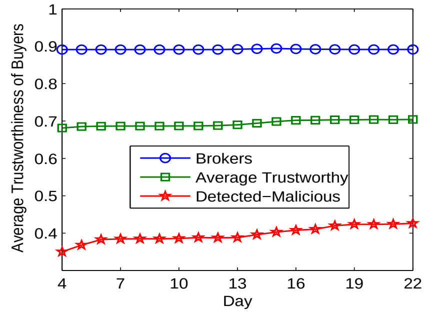

Fig. 9: Trustworthiness of Buyers in Different Roles

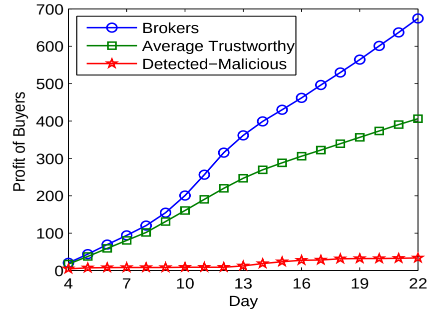

Fig. 10: Profit of Buyers in Different Roles

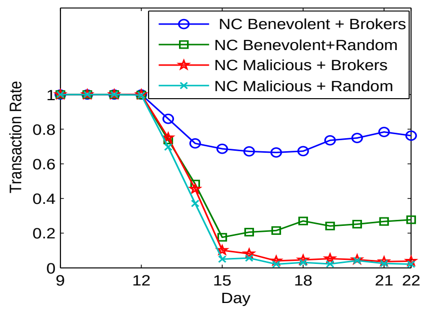

Fig. 11: Transaction Rate of Newcomers

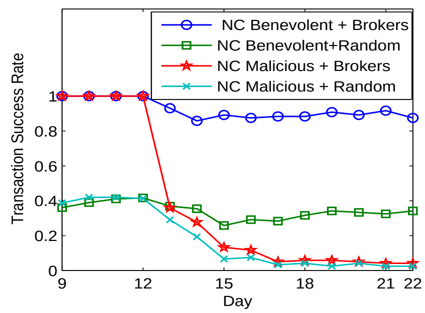

Fig. 12: Transaction Success Rate of Newcomers

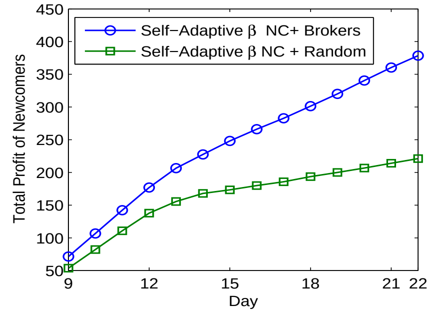

Fig. 13: Profit of Newcomers

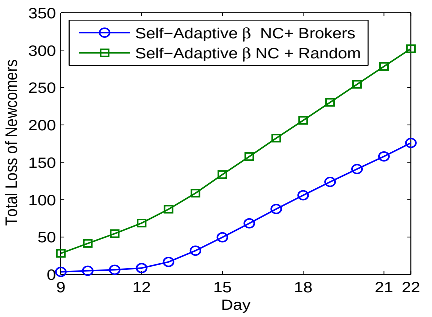

Fig. 14: Loss of Newcomers

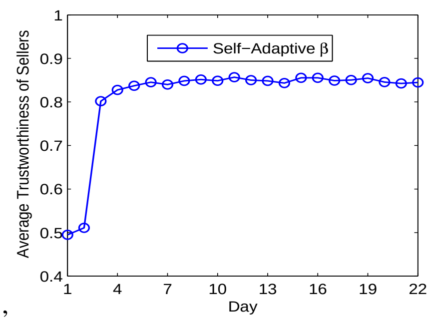

Fig. 15: Trustworthiness of Sellers with Adaptive β

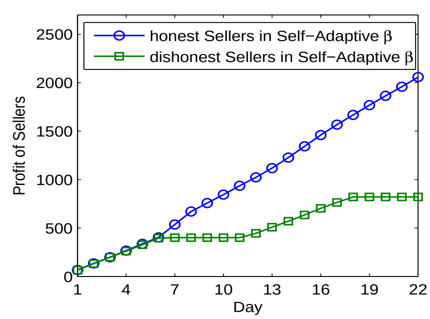

Fig. 16: Profit of Sellers with Adaptive β

much as twice the profit than those newcomers who adopt brokers, which shows that the first group of newcomers can more accurately predict the excepted utility of sellers.

Finally, we compare the average trust values as well as the profits of different sellers. Results indicate that buyers conduct business transactions with more trustworthy sellers after establishing their advisers network-staring at day 3 (Figure 15). Besides, according to Figure 16, honest sellers conduct more transactions with buyers and gain more profit. This is because buyers filter away dishonest advisers and therefore malicious sellers will have a low chance to be recommended to them. Thus, sellers would be better off if they are honest.

VI. Related work

Different incentive mechanisms have been proposed to supplement the advantages that reputation systems bring to e-marketplaces. Jurca [7] proposed a side-payment mechanism which makes truthful behavior the best interest of rational agents in e-maketplaces. This mechanism offers side payment to buying agents that fairly rate the outcome of businesses with sellers. In the side payment mechanism, buyers could gain the maximal reward (side-payment) through providing truthful ratings, assuming that they act independently and do not collude in giving unfair ratings. To deter coalitions, Jurca and Faltings [8] further enhanced the side payment mechanism so that honest buyers can achieve the minimal cost imposed on the marketplace owner, which discourages agents from conducting a collusive attack.

Zhang and Cohen [23] proposed a trust-based incentive mechanism where sellers prefer to provide more attractive products to honest buyers. The key idea is that, since an honest buyer is most likely the neighbour of many other buyers, if that buyer is satisfied with the products, she promotes the sellers by propagating the positive feedback to its social network (neighbours), which helps the sellers to attract more potential buyers.

The credibility mechanism in [18] delivered another type of incentive mechanisms in which buyers and sellers receive punishment if they provide asymmetric ratings about the conducted transactions. They would be prevented from conducting transactions for some period, which is inversely determined by their level of credibility.

The SocialTrust incentive mechanism elicits truthful ratings from buyers in social e-commerce. The distributed nature of social e-commerce systems requires buyers to subjectively build their advisers networks with minimum intervention of the central authority, distinguishing SocialTrust from other approaches. Unlike other mechanisms, here, in SocialTrust, the central server acts as an ultra-organizer entity which monitors the performance of the market and recommends new calibrated value of the credibility threshold to buyers so that they can re-evaluate their advisers network, adapting to the current state of the market.
To overcome the bootstrapping problem of newcomers, SocialTrust incentivises some amongst the credible advisers to become brokers and sell reputation information to newly joined buyers. Besides, dishonest advisers who are unanimously voted by buyers are punished by releasing their identity to all participants, resulting in their deprivation from accessing honest feedback in future purchases.

VII. Conclusion and Future Works

In this paper, we proposed a self-enforcing incentive mechanism which stimulates the altruistic attitudes of buyers through proper reward and punishment schema. Buyers choose to honestly share their experiences with others to obtain maximal utility. The agent of each buyer would firstly adopt the existing trust metrics (e.g. Prob-Cog) to build an adviser social network for its buyer. The agents also submit the lists of the most credible and the least credible advisers along with other information (i.e., transaction rate and transaction success rate) to the central server. Given this information, the central server, on the one hand, adaptively adjusts the credibility threshold for buyers according to the market performance, helping them to detect and identify malicious advisers more effectively, and on the other hand, rewards the most credible advisers and punishes the least credible advisers in the e-marketplace through the Borda count voting procedure.

Comparative experiments indicate the efficacy of the adaptive threshold-setting (SACTAM) mechanism in improving the performance of social commerce. Experimental results further show the effectiveness of the voting mechanism in promoting honesty and discouraging dishonesty attitudes among participants. Beside the social fame and economic advantages, the privileges awarded to the most trustworthy buyers can effectively address the bootstrapping problem of newcomers.

An interesting direction for future work would be to improve the threshold setting mechanism by adopting different dynamic performance metrics supported in the market microstructure literature [12], in addition to those considered here. Furthermore, since buyers' honest collaboration with the central server is essential to monitor the performance of the marketplace, a useful direction for future work would be the evaluation of the SocialTrust mechanism with different levels and different quality of participation from buyers.

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